Worth the Risk? The Performance of Banks Reliant on CLO Funding

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Abstract

We propose an empirical strategy based on a shift-share approach to identify bank-level institutional funding shocks in the collateralized loan obligations (CLO) market. We apply our methodology to study the effects of CLO funding on bank riskiness. We find that bank riskiness decreases for two quarters in response to a positive shock to CLO funding. Banks increase the origination of institutional loans, while retaining lower amounts of loans on their balance sheets. This reduces exposure to credit risk. At the same time, banks use resources more efficiently, as the generation of non-interest income and the overall income generation process strengthen. The performance of the retained loans also marginally improves, further strengthening banks' financial positions.

Keywords: CLOs, Institutional Loans, Institutional Investors, Bank Risk, Bank Performance.

JEL Classification: G21, G23, G32.

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We thank Alberta Di Giuli, Tommy Murphy, Fabiana Penas, Martín Rossi, and Federico Sturzenegger for helpful comments and insights. Any remaining errors or omissions are our own.

1 Introduction

Shadow banking facilitates the flow of funds made available by institutional investors to the banking sector. As the role of the shadow banking system in financial intermediation and the originate-to-distribute (OTD) model of banking grow, understanding the causal effects of the availability of institutional investors funding on banking outcomes becomes of paramount importance. However, this is a challenging endeavor due to the difficulty isolating exogenous variations in the institutional investor demand for bank-mediated investment opportunities necessary to correctly disentangle these effects.

In this paper, we propose a novel approach to tackle this task for the institutional funding conveyed to banks through the collateralized loan obligations (CLOs) market, arguably one of the primary asset classes in the shadow banking system representing close to one-third of all commercial and industrial (C&I) loans outstanding in the United States.[1] The approach defines an exogenous measure of CLO funding at the bank level, relying on an interacted variable in the spirit of shift-share empirical designs (Borusyak, Hull, and Jaravel, 2022; Bartik, 1991; Blanchard and Katz, 1992; Autor, Dorn, and Hanson, 2013; Nunn and Qian, 2014) in which the time-series component is provided by a Vector Autoregressive (VAR) model used to identify a sequence of structural shocks to the institutional investor demand for institutional loans acquired via CLOs.

As an illustration and a contribution to the current literature that studies the CLO market and its impact on bank performance, we apply this methodology to estimate the effect of CLO funding on bank riskiness. However, our empirical strategy could be easily implemented to other variables of interest. The primary motivation for concentrating on this aspect of bank performance is the premise that reliance on CLOs may help banks reduce their riskiness by optimizing the use of resources to support credit origination and manage the related credit risks.[2]

[1] Authors' calculation as of 2021, based on outstanding CLOs estimates (reported by Bloomberg in two recent articles on May 28 and July 8, 2021) and total C&I loans data from the Board of Governors of the Federal Reserve System.

[2] Anecdotal evidence suggests that this is actually part of the reasons why banks rely on CLOs. For instance, JPMorgan Chase & Co.'s 2020 Form 10-K states: *"Management of the Firm's wholesale credit risk exposure is accomplished through a number of means, including: [l]oan underwriting and credit approval process, [l]oan syndications and participations, [l]oan sales and securitizations..."*

The effect on bank performance of relying more on CLO funding ultimately depends on banks' ability to distribute loans originated with the final intent to sell them on the CLO market, transferring the risks associated with the additional origination of these loans and generating income from the related fees. Two main determinants are at play.

First, securitization may have detrimental effects on bank lending standards and the incentives to monitor bank credits. Since banks retain part of the institutional loans they syndicate, this may lead to a deterioration of their portfolios. While this result is well documented in the literature for mortgage backed securities before the financial crisis (e.g., Mian and Sufi, 2009; Keys, Mukherjee, Seru, and Vig, 2010; Nadauld and Sherlund, 2013), however, it is far less definite for CLOs with Bord and Santos (2015) suggesting that CLO funding can result in weakening lending standards and Benmelech, Dlugosz, and Ivashina (2012) finding the opposite.

Moreover, an increased availability of CLO funding would not change the incentives for a bank already operating within the OTD model. Nevertheless, additional CLO funding can still affect bank loan decisions on the intensive margin through a substitution of institutional business loans for loans not intended for distribution. If institutional business loans are of lower quality, holding more of them on their balance sheet would imply higher bank default risk. However, as said above, it is not fully clear whether institutional business loans perform worse than unsecuritized loans, and this channel would be muted if they are not worse.

Second, there is the advantage of risk transfer. Even if CLO funding does lead to worse loan performance, banks could still weather the consequences of it if they succeed in transferring the related credit risks. The literature, however, is not unambiguous on this point either. On the one hand, evidence suggests that banks retain less institutional business loans on the primary syndicated market (Bord and Santos, 2015) and that loan sales on the secondary market can be an helpful risk management tool (Drucker and Puri, 2009). On the other hand, the literature on other securitization vehicles casts some doubts about how generally applicable this result is (see, for instance, Acharya, Schnabl, and Suárez, 2013).

What the net effect of these two factors is and in which way CLO-funded lending affects bank riskiness remains an open question. We find that an exogenous increase in bank CLO funding indeed decreases bank riskiness, captured by a falling expected default frequency, for about half a year, with the largest effect after one quarter. We also document the mechanism through which loan securitization reduces bank riskiness. We identify three main channels. First, in the wake of an increase in institutional investors' appetite for business loans, banks ramp up loan origination, fostering net non-interest income and improving the income origination process. Second, banks also reduce the amount of C&I loans outstanding on their balance sheets, despite the boost in the origination of loans, thus reducing credit risk exposure. And, lastly, the performance of the remaining loans on their balance sheets temporarily improves as well.

1.1 Markets, Market Participants, and Identification Strategy

Our study relies on the intrinsic relation between the syndicated loan market and the CLO market to device an estimation strategy of the effects of CLO funding on bank riskiness. A stylized representation of the interactions between these markets and their participants is illustrated in Figure 1.

In the OTD model of banking, CLOs funded by institutional investors ultimately fund syndicated institutional loans originated by banks.[3] In a representative case, a lead bank arranges a loan to a corporate borrower and distributes this loan on a pro rata basis among syndicate participants – the Primary Market (1) in Figure 1.

These loans can next be traded in a secondary market, where CLOs constitute a prominent group among the market participants. Institutional loans are predominantly term loans with characteristics specifically designed to appeal to institutional investors, including bullet repayment and penalizations for early repayment. CLOs fund the acquisition of loans

[3]Our explanation here applies to cash and arbitrage CLOs which are unrelated to banks, as opposed to balance sheet CLOs sponsored by banks. In an arbitrage CLO, a portfolio manager acquires loans that have been originated by third parties, and funds the transaction primarily by issuing floating-rate notes paying lower rates than those on the underlying loans. The portfolio manager, which often retains at least part of the CLO equity, is thus said to arbitrage the spread between the yields on the structure's liability tranches and the ones on the loans. By contrast, in a balance sheet CLO, a loan originator such as a bank, sponsors a bankruptcy-remote special purpose vehicle (SPV) that buys the loans from the bank. The SPV sells the CLO liability tranches, retaining the equity portion, and is then consolidated onto the balance sheet of the bank. The transaction is meant to provide financing to the loan originator and reduce its capital requirements in the case of regulated banks. By industry estimates, arbitrage CLOs account for 90 to 95% of the CLO market. See Fitch Ratings (2022) for further details.

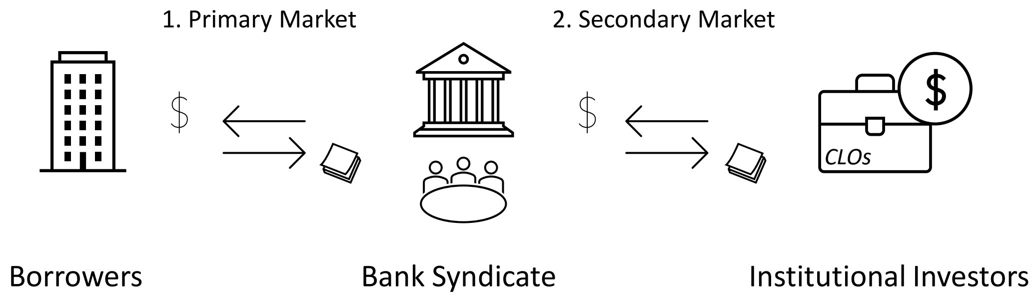


Figure 1: Origination and Securitization of Syndicated Loans: Loans originated by conventional banks for Corporations are securitized, transformed into CLOs, and sold to Institutional Investors.

through the sale of CLO tranches to a large base of sophisticated investors, providing a securitization vehicle through which institutional investors can efficiently buy into the future cash flows of diversified portfolios of institutional loans. The institutional investors include insurance companies, mutual funds, pension funds, endowment funds, among others. This is the Secondary Market (2) in the figure.

Institutional investors find in CLOs a convenient way to indirectly invest in corporate loans, as CLOs offer tranches taylored for different risk profiles and can be traded readily. As the institutional investors' appetite for risky assets changes over time, so does their demand for CLOs. An increase in appetite for these assets translates into more acquisitions of CLO tranches, which in turn provides CLO managers with the funding necessary to acquire more loans. Ultimately, lead arrangers find improved market conditions to originate and fund more new institutional loans.

To answer the main research question of the paper, it would be sufficient to estimate a panel model of the form:

$$BankRisk_{i,t} = \alpha_i + \beta CLOFunding_{i,t} + \Phi Controls_{i,t} + \upsilon_{i,t}, \tag{1}$$

provided we had both a suitable measure of bank riskiness and exogenous variations in CLO funding.

The literature offers several alternatives to gauge bank default risk. We adopt a measure of expected default frequency building on Merton (1974)'s bond pricing model that has been extensively applied in both academic and industry works. Measures of plausibly exogenous variation of CLO funding are not readily available, though. The approach we propose for the identification of β in (1) is based on an interacted time-series/cross-section, in which the time series component is obtained exploiting the credit markets structure discussed above.

Our approach combines, then, two components. The first component captures variation on the time dimension. We employ a VAR model to jointly represent the structure of the institutional loan and CLO markets. The transmission mechanism of institutional investor demand shocks for CLOs to loan origination is identified by sign restrictions. The identification relies on the transmission channel that takes place in the CLO secondary market.[4] Once we have identified this shock, the second component we use is a measure of bank reliance on the CLO market to fund the origination of loans, which embeds cross-sectional heterogeneity. The resulting interacted variable can be thought of as a measure of treatment intensity, conditional on time fixed effects, bank fixed effects, and a set of predetermined observable bank characteristics.

Finally, we use the local projections method of Jordà (2005) to estimate the causal effects of CLO funding on expected default frequency and other measures of bank performance at quarterly frequency and up to a one-year horizon. We find that, one-quarter after a one-standard deviation shock to the institutional investor demand for CLOs, the expected default frequency of a bank falls by about 17 basis points for each additional percentage point in the average share of institutional loans to all loans arranged by the bank, our measure of

[4]Historically, banks have been the main participants in the syndication process, although more recently institutional investors have started participating in the syndication process directly or through CLOs (this channel is studied by Bord and Santos, 2015, for instance). Two types of institutional demand shocks for institutional loans may then coexist. Lead arranger banks, however, would likely respond to a primary market institutional demand shock by expanding the syndication activity, rather than substituting institutional syndication participants for secondary market CLOs. In terms of our identification approach, the primary market shocks would affect the issuance of institutional loans without a direct impact, or an impact similar to a loan supply shock, on the secondary market CLOs price. The two forms of institutional investor demands would hence be identified separately in our benchmark model, with the primary market shock being absorbed by the fourth residual shock of the model. Since the effects of the primary market shocks on bank riskiness would arguably have the same direction as those documented here, by focusing on the secondary market channel the results of our approach can be regarded as providing at least a conservative lower-bound estimate of the total effects of the institutional investor demand.

bank exposure to CLO funding.

1.2 Related Literature

Our work speaks to various strands of the literature in financial intermediation, credit markets, and securitization. It also relates to the modern empirical literature using mixed micro-macro data and methods to identify causal effects in a panel framework of analysis.

Our paper closely relates to the literature on the effects of the sale of business loans on bank behavior (which includes, among others, Gorton and Pennacchi, 1995; Boot, 2000; Parlour and Plantin, 2008; Drucker and Puri, 2009; Gande and Saunders, 2012; Li, Saunders, and Shao, 2015; Loutskina, 2011; Parlour and Winton, 2013; Shleifer and Vishny, 2010).

A common theme in this literature is whether loan sales affect bank incentives to perform their traditional screening and monitoring roles, potentially conditioning loan, borrower, and lender performance. Another strand of this literature focuses on the use of securitization in bank risk management. Loutskina (2011) and Shleifer and Vishny (2010) show that bank loan origination and bank balance sheets adjust in response to changes in market conditions, a result consistent with our findings. The procyclical response of loans exacerbates both the upside and downside of the economic cycle.

Our work also relates to the literature studying how the marketability of business loans can affect the supply of credit. In particular, Ivashina and Sun (2011) and Nadauld and Weisbach (2012) have shown that institutional investors and securitization can indeed shift the supply of credit – which is an element of relevance to develop our identification strategy. Moreover, our work also relates to the literature on CLO funding and lending standards (Benmelech, Dlugosz, and Ivashina, 2012; Bord and Santos, 2015), which has thus far yielded mixed evidence.

Similarly, our research is also related to extant works studying the role of securitization on bank performance, such as Casu, Clare, Sarkisyan, and Thomas (2013) which, using pre-crisis data and a broad definition of securitization, does not find a strong relationship. We depart from extant works by focusing solely on the securitization of business loans via CLOs in the post-financial crisis period, with a market operating under a new regulatory framework and encompassing new market participants and institutions. All of these differences make it plausible to expect also a different relation between securitization and bank performance.

On a more general level, our work contributes to the literature on shadow banking and the shift of banking towards an OTD model, a strand that has developed significantly in the last decade to include works like Gorton and Metrick (2012); Pozsar, Adrian, Ashcraft, and Boesky (2013); DeYoung (2014); Culp and Neves (2017); Adrian, Aschcraft, Breuer, and Cetorelli (2019); Boot and Thakor (2019), to name but a few.

Lastly, on the empirical grounds the methodology we propose draws principles from the applied econometric work both in micro and macroeconomics. Interacted variables have been extensively used, especially as instrumental variables, in different empirical micro-econometric applications in labor economics (Bartik, 1991; Blanchard and Katz, 1992; Autor, Dorn, and Hanson, 2013; Acemoglu and Restrepo, 2020) and development economics and international aid (Werker, Ahmed, and Cohen, 2009; Nunn and Qian, 2014; Nizalova and Murtazashvili, 2016). At the same time, mixed identification strategies have been used to identify the effects of monetary and fiscal policies in macro-econometric models (Blanchard and Perotti, 2002; Romer and Romer, 2004, 2017). Our empirical strategy shares the spirit of these papers, yet it provides a novel approach by taking the information obtained from a structurally identified VAR model to construct the interacted variable used as a regressor in the main panel model.

2 Empirical Methodology

In this section we describe the empirical methodology that leads to the estimation of model (1) and of the impulse response functions of the default risk probability to bank CLO funding by local projection (Jordà, 2005).

2.1 Measuring Default Risk

We start with the construction of the default risk probabilities that constitute the left hand side variable of model (1).

The measure we use is the expected default frequency, an application of Merton

(1974)'s bond pricing model pioneered by KMV (later acquired by Moody's), designed to gauge a firm's distance-to-default. This application is has been extensively used both in the industry and the academic literature (see, for instance, Vassalou and Xing, 2004; Duffie, Saita, and Wang, 2007; Campbell, Hilscher, and Szilagyi, 2008; Bharath and Shumway, 2008).

The distance-to-default, DD_t, can be thought of as a firm's market net-worth standardized by its asset volatility:

$$DD_t = \frac{A_t - L_t}{A_t \sigma_A}, \tag{2}$$

where A_t is the market value of the assets of the firm at time t, L_t the value of its liabilities, and σ_A is the standard deviation of the annual percentage change of A_t.

The approach models the value of the equity of a firm as the price of a perpetual call option on A_t with strike price given by L_t. A firm is considered in default when the value of assets falls below that of liabilities, i.e. when $DD_t < 0$. Applying option pricing theory, knowledge of today's assets value A_t and of the return volatility σ_A allows us to calculate the probability that $DD_T < 0$ in period $T > t$, under some distributional assumptions about the underlying stochastic process of A_t.

The expected default frequency, EDF_t, is then defined as

$$EDF_t = Pr(DD_T < 0 | DD_t), \tag{3}$$

where T is usually taken to be $t + 12$ months.

Computing the probability in (3), it must be noted, entails some challenges. The most important one arises from the fact that data on A_t and σ_A are not directly observable. Hence, they must be inferred from other available data –noticeably, the value of equity, its volatility, the value of liabilities, and the risk-free rate– and their relations within an option pricing model.[5] A second challenge stems from the frequency of data available. While market data, such as the risk-free rate, can be available at daily frequency, other data, such as the book value of liabilities, can be available at quarterly frequency only. These elements can potentially cause EDF to be noisy. Nonetheless, as illustrated in Section 3, our EDF

[5]See, for instance, section 2.1 in Bharath and Shumway (2008) for a detailed exposition.

measure closely correlates in aggregate with well-established indicators of financial stress.

2.2 Measuring CLO Funding

The second piece necessary for the estimation of model (1) is the construction of the CLO funding variable on the right-hand side of the panel regression. We propose a strategy inspired by Borusyak, Hull, and Jaravel (2022)'s shift-share instrumental variable approach, encompassing as special cases Bartik-like instruments in the vein of Bartik (1991). As noted by Borusyak, Hull, and Jaravel (2022), this approach is not limited to instrumental variables only, but it also extends to reduced form regressions – as is our case. Similarly, although originally developed to work with multiple shocks, it applies regularly to a single-shock environment as well.

The key insight in our case is to obtain a plausibly exogenous shift component from a structural VAR model to form the desired regressor by combining it with a cross-sectional share component allowed to be endogenous. The interaction between these two elements yields an exogenous factor at the panel level and OLS estimates of this model are consistent under a set of relatively mild assumptions laid out by Borusyak, Hull, and Jaravel (2022).

We discuss these assumptions in detail in Section 2.3. It is worth emphasizing at this point, however, that the consistency of the estimator in our strategy relies on the exogeneity and independence of the shock (as in Borusyak, Hull, and Jaravel, 2022), in contrast to the alternative approach to shift-share which relies on the exogeneity of the share component instead (as in Goldsmith-Pinkham, Sorkin, and Swift, 2020).

Let $\overline{E}_i$ and S_t respectively indicate the cross-section and time-series components of the shift-share term. We define the CLO funding measure as:

$$CLOFunding_{i,t} = \overline{E}_i \times S_t. \tag{4}$$

$\overline{E}_i$ represents the relevance of institutional loans in the mix of loans led by bank i throughout the entire sample period. As CLOs are key buyers of institutional loans, this provides a cross-sectionally heterogenous measure of bank reliance on CLO funding. Let $E_{i,t}$ be the proportion of institutional loans to all loans arranged by bank i in quarter t and T_n

the time sample size, $\overline{E}_i$ is simply defined as the sample average of $E_{i,t}$:

$$\overline{E}_i = \frac{1}{T_n}\sum_{t=1}^{T_n} E_{i,t}.$$

In order to identify S_t, the structural institutional investor demand shock for institutional loans taking place through the CLO market, we resort to a small-scale VAR model.[6] This VAR model provides a stylized representation of the institutional loan market previously described in Section 1.1 and Figure 1, and can be specified with the following vector of four endogenous variables, Y_t:

$$Y_t = \begin{bmatrix} CLOPrice_t \\ LoanVolume_t \\ LoanSpread_t \\ KCStress_t \end{bmatrix}, \tag{5}$$

where $CLOPrice_t$ is the price level of investment opportunities in the market for corporate loan-backed securities, i.e., a price index for the CLO liability tranches traded in the secondary market; $LoanVolume_t$ is the aggregate volume of new institutional loans originated by the banking sector; $LoanSpread_t$ is the spread associated with those new institutional loans; and $KCStress_t$ is the Kansas City Financial Stress Index. We leave for Section 3 a more detailed discussion of the sources and construction of these variables.

The reduced-form VAR model of order p can be written as:

$$Y_t = \sum_{l=1}^{p} B_l Y_{t-l} + u_t$$

where B_l is a matrix of parameters and the reduced-form VAR residuals are collected in u_t. Let A_0 be the structural impact matrix that linearly relates the structural shocks of the VAR

[6] The financial literature has previously resorted to VAR models to study the dynamics of the corporate loan market. See, for instance, Barraza, Civelli, and Zaniboni (2019).

$$\begin{bmatrix} u_t^{clo} \\ u_t^{vol} \\ u_t^{spr} \\ u_t^{kcs} \end{bmatrix} = \begin{bmatrix} + & - & - & * \\ + & + & + & * \\ - & - & + & * \\ * & * & * & * \end{bmatrix} \begin{bmatrix} w_t^{InstD} \\ w_t^{BankS} \\ w_t^{CorpD} \\ w_t^{Resid} \end{bmatrix}$$

Table 1: Identifying restrictions of the monthly structural shocks of the VAR model. The four shocks identified are an institutional investor demand shock for institutional loans w_t^{InstD}, a bank supply shock w_t^{BankS}, a corporate demand shock w_t^{CorpD}, and a catch-all residual shock w_t^{RESID}. The symbols $+/-$ indicate a positive/negative on-impact sign restriction and $*$ indicates unrestricted coefficients.

model, w_t, to the reduced-form residuals, u_t:

$$u_t = A_0 w_t. \tag{6}$$

We estimate the reduced-form VAR using Bayesian techniques with Normal-Wishart priors and $p = 6$ lags, at monthly frequency, and we identify the structural shocks w_t by use of sign restrictions on the elements of A_0.[7] Table 1 illustrates the identification assumptions.

We adopt a supply/demand identification logic conceptually similar to the strategy implemented in Kilian and Murphy (2012) and Inoue and Kilian (2013) to identify supply and demand shocks in the oil market.[8] The motivation of the shocks in our model, however, relies on the dual nature of the institutional loan market discussed in Section 1.1. In this market, banks originate loans with the twofold goal of lending to the corporate sector as well as selling these loans to CLOs funded by institutional investors.

The core piece of our identification strategy is defined by the upper-left 3×3 sub-matrix of A_0. We use this block to characterize the bank supply of institutional loans, structurally identified by shock w_t^{BankS} in Table 1, pivoting between the corporate demand for institutional loans and the institutional investor demand for institutional loans taking place through the CLO secondary market, identified by shocks w_t^{CorpD} and w_t^{InstD} respectively.

The identification scheme of w_t^{InstD} is defined by the first column of this 3×3 sub-block

[7] We perform the estimation procedure using the econometric package developed by Dieppe, Legrand, and van Roye (2016).

[8] See Canova (2007) and Kilian and Lütkepohl (2017) for details on identification using sign restrictions.

of A_0. A positive institutional investor demand shock increases on impact the price of CLOs, increases the origination of institutional loans, and decreases the loan spreads at issuance. These effects of institutional investors and CLOs on the conditions in the corporate loan market are empirically supported by findings in Ivashina and Sun (2011) and Nadauld and Weisbach (2012). We interpret this as a liquidity shock in the CLO market, whereby investors make more funds available to CLO managers and in so doing stimulate the origination of institutional loans to be acquired by CLOs.

Similarly, the second and third columns of the sub-matrix identify w_t^{BankS} and w_t^{CorpD}. A positive bank loan supply shock is assumed to have a negative impact on the price index of CLOs (as more loans and CLOs are made available), a positive effect on the origination of new institutional loans, and a negative impact on the spreads corporations pay to borrow these loans from the banking sector. On the other hand, a positive corporate demand shock for institutional loans is assumed to make the CLO index fall (again, as more loans and CLOs are available) and to increase the origination of institutional loans and the loan spreads.

The inclusion of a fourth variable in the VAR model allows us to recover a fourth structural shock, which we use to further refine the estimation of the three previously discussed shocks. This fourth shock, w_t^{Resid}, is a residual shock that captures the effect on the system dynamics of other aggregate shocks not explicitly identified by the first three structural shocks in the model.[9] The fourth column of A_0 illustrates the restrictions of w_t^{Resid} are left unspecified.

Since the response of financial riskiness to the liquidity shock is intrinsically related to our research question, we take an agnostic stance and leave the sign of this restriction unspecified. For similar reasons, we also leave unrestricted the signs of the effects of w_t^{BankS} and w_t^{CorpD} on financial riskiness.

2.3 Panel Model and Local Projections

The final step of the empirical methodology is the estimation of the impulse response function by using the local projections method. This approach constructs a response function by simply tracking the estimates of β in the panel model at different lags of the interaction

[9] See Kilian and Murphy (2014) for a similar application.

term (see Jordà, 2005).

More precisely, we consider the following specification of model (1):

$$EDF_{i,t+j} = \alpha_i^j + \gamma_t^j + \beta^j(\overline{E}_i \times S_t) + \sum_{k=1}^{K} \phi_k^j(\overline{E}_i \times S_{t-k}) + \sum_{k=1}^{K} \theta_k^j EDF_{i,t-k} + X_{i,t-1}\Gamma + \varepsilon_{i,t}^j, \quad (7)$$

where the i and t subscripts denote banks and time periods; α_i and γ_t respectively indicate bank fixed effects and quarter fixed effects; $\overline{E}_i$ is our measure of bank reliance on the CLO market; S_t is derived from the structural institutional investor demand shock by aggregating w_t^{InstD} quarterly; $X_{i,t-1}$ is a vector of bank-specific controls and $\varepsilon_{i,t}$ is the error term. Finally, script j with $j = 0, 1, ..., J$ tracks the coefficient β^j for the estimation of the local projections up to horizon J. In our benchmark application, we take $K = 1$ quarter and $J = 4$ quarters. The model is estimated by least squares.[10]

The vector of bank-specific controls, $X_{i,t-1}$, includes a set of variables found by Casu, Clare, Sarkisyan, and Thomas (2013) to be relevant determinants of the bank decision to securitize, namely: real estate loans to total loans; commercial & industrial loans to total loans; deposits to total assets; noninterest income to net operating revenue; the log of total assets; and the growth rate of total loans. It also includes a measure of balance sheet liquidity, as Loutskina (2011) has shown this is related to securitization. The measure is inspired by Kashyap and Stein (2000) and is computed as the sum of securities available for sale, federal funds sold in domestic offices and securities purchased under agreements to resell, scaled by total assets. The last variable in this vector is the ratio of equity to total assets, as this can naturally affect both lending and risk. In all cases, these controls are lagged by one quarter.

Borusyak, Hull, and Jaravel (2022) show that a shift-share model can be equivalently recast as a regression aggregated at the shock-level by using as weights each shock's average exposure across observations. Estimates consistency of this regression relies on the orthogonality of shocks and exposure-weighted residuals. This condition is satisfied as long as shocks are as-good-as randomly assigned and mutually uncorrelated, there is a large number

[10]Equation (7) is a dynamic panel with large T with respect to N, which renders least squares a suitable estimation method (see, for instance, chapter 8 in Baltagi, 2013). Romer and Romer (2017), for instance, also estimate a model equivalent to that in equation (7) by OLS.

of observations (many shocks), and the average exposure weights are sufficiently dispersed.[11]

Although the shift-share approach is primarily used for instrumentation in cross-section regressions, it also applies to reduced-form and panel models. Moreover, it also accommodates cases in which only one shock is available for long time series. Therefore, the OLS estimates of β^j in Equation (7) are consistent if the assumptions of the quasi-experiment framework of Borusyak, Hull, and Jaravel (2022) are satisfied. Specifically, these requirements are as follows.[12]

First, the shocks S_t must be quasi-randomly assigned and serially uncorrelated conditionally on a set of shock-level observables. In our empirical strategy, meeting these two conditions primarily builds on the structural identification of w_t^{InstD} from the VAR model in Section 2.2.

The identification strategy generates exogenous, zero-mean, uncorrelated investor demand shocks which are orthogonal to other factors that can affect bank investment decisions and, consequently, bank riskiness, especially the loan supply shocks w_t^{BankS} in the VAR. The aggregation of the monthly VAR shocks w_t^{InstD} to obtain S_t at quarter-level does not tamper with these properties. Moreover, the inclusion of the vector of bank-level control variables in the panel model, controlling for observable bank characteristics that might affect the decisions to originate institutional loans, and the use of both bank and quarter fixed effects help mitigate the concerns that S_t may still be correlated with other confounding factors which are not explicitly accounted for in the stylized VAR model of the institutional loan market.[13]

Unit and period fixed effects are particularly important for the conditional quasi-random assignment property of the shocks in the panel shift-share model. The unit fixed effects, α_i, in combination with the use of time-invariant shares, $\overline{E}_i$, control for the time-invariant unobservables in the residuals of equation (7) as well as the time-invariant compo-

[11]These conditions are formally introduced in Assumptions 1 and 2 and Propositions 2 and 3 of Borusyak, Hull, and Jaravel (2022). Assumptions 3 and 4 and Propositions 4 generalize the result by allowing for shock expectations to depend on observables and for weak mutual dependence, which are relevant cases in panel models.

[12]See Section 4.3 of Borusyak, Hull, and Jaravel (2022) for a discussion of the shift-share approach in the panel context. We also illustrate the shocks orthogonality condition that applies to our specific model and the requirements for consistency in Appendix C.1.

[13]For instance, the general liquidity stance of financial markets due to changes in the policy rates may affect the level of riskiness of the bank sector and still be correlated with S_t. Period fixed effects would conveniently control for this factor in the panel regression residuals.

nent of S_t. The period fixed effects, γ_t, control for any omitted source of common period-specific variation in the panel residuals as well as the within-period variations in the single shock S_t.[14]

The second requirement is that the large number of observations required for consistency must come from the size of the sample when only one shock is considered and for a small cross-section. Our panel model (7) is estimated over 26 quarterly observations. Finally, the third requirement is that the shock does not disproportionately affect any of the banks in the sample, that is a small average exposure share is expected. The shares $\overline{E}_i$ reported in Table A2 also support this last requirement.

Intuitively, the use of the interaction term $\overline{E}_i \times S_t$ is similar to a *difference-in-differences* estimation strategy, where the estimates compare the default risk of banks that rely more heavily on institutional investors to banks that rely less on institutional investors to fund loans, in periods following high institutional demand pressure relative to periods following low institutional demand pressure for loans, as Nunn and Qian (2014) notice in their application.[15]

3 Data Sources and Elaboration

Bank Data. To construct the bank-level *EDF* measure for the panel model, we use market data from the Center for Research in Security Prices (CSPR) and balance sheet data from Standard & Poor's COMPUSTAT, and we follow the input definitions and estimation procedure described in Bharath and Shumway (2008).[16]

To check that *EDF* adequately reflects bank riskiness over time, we calculate an aggregate *EDF* series for the U.S. domestic banking sector as the average *EDF* for all U.S.-

[14] It is interesting to note that this requirement resembles the condition for a consistent estimation of model (7) in Nizalova and Murtazashvili (2016) as well. They show that the OLS estimates of β^j are consistent as long as the source of heterogeneity among individuals, $\overline{E}_i$, and the residual $\varepsilon^j_{i,t}$ of the panel controlling for unit and period fixed effects are jointly independent of the treatment, S_t in this case.

[15] A similar approach where a measure of exposure with cross-sectional heterogeneity is interacted with a time series like in equation (7) can also be found, for example, in Kashyap and Stein (2000) and Loutskina (2011).

[16] As noted by the authors, this is the same approach employed by Vassalu and Xing (2004); Duffie, Saita, and Wang (2007); Campbell, Hilscher, and Szilagyi (2008), and others. Bohn and Crosbie (2003) provide an intuitive description of the main elements of this application of the option pricing theory.

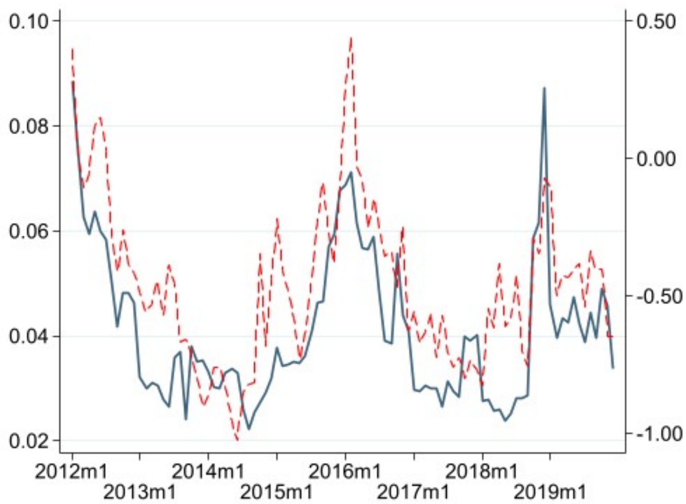


Figure 2: Monthly Average Expected Default Frequency of U.S.-based Financial Firms (solid blue line, left axis) and Kansas City Financial Stress Index (dashed red line, right axis), 2012-2019 period.

based financial companies – Standard Industrial Classification (SIC) codes between 6000 and 6999 – and we plot it along with the Kansas City Fed Financial Stress Index in Figure 2. It is reassuring to find that the variables move closely together, showing a correlation coefficient of 0.8.

We also use bank-level data from the FR Y-9C reports provided by the Board of Governors of the Federal Reserve System. This data set accounts for the majority of the control variables we use in the panel analysis and, also, a number of dependent variables we discuss below. For the sake of brevity here, we refer the reader to Section A in the Appendix for a thorough description of the sources and construction of these variables.

Loan Data. Our data on business loans include all facilities syndicated in the U.S., issued by U.S. firms, and in U.S. dollars between January 2012 and December 2019 from the Thomson Reuters LPC DealScan data set. When we refer to institutional loans, we refer to all term loan B through term loan K facilities from this set. Institutional loans represent 33% of all term loans in the sample and account for 55% of their dollar amount. Term loans B, we shall add, represent 98% of the institutional loans.

In forming the panel data set used for the local projection analysis, we must first take into account the fact that large banks often arrange deals through multiple subsidiaries. Hence, we start by consolidating at the top Bank Holding Company (BHC) or Financial Holding Company (FHC) level all lead arrangers belonging to a same organization.[17] Given that riskiness is intrinsically related to the regulatory framework banks are subject to and that *domestic* and *foreign* banks have been subject to different regulations over time, we focus our analysis on *domestic* BHCs and FHCs only. The process of loan and bank aggregation thus yields a first sample of 28 top banks originating at least 50 loans during the sample period, which earned in aggregate $10,531$ lead arranger credits in institutional loans.

As we intend to study the effect of CLO funding on bank performance, we set a minimum level of reliance on this market to deem a bank relevant to our study. We retain then in our panel only top lenders for which institutional loans constitute at least 5% of the loans they lead during the sample period. This leaves us with 16 top banks taking $10,106$ lead arranger credits in institutional loans.[18] Table A2 in the Appendix lists these lead arrangers and their corresponding measure of reliance on CLO funding.

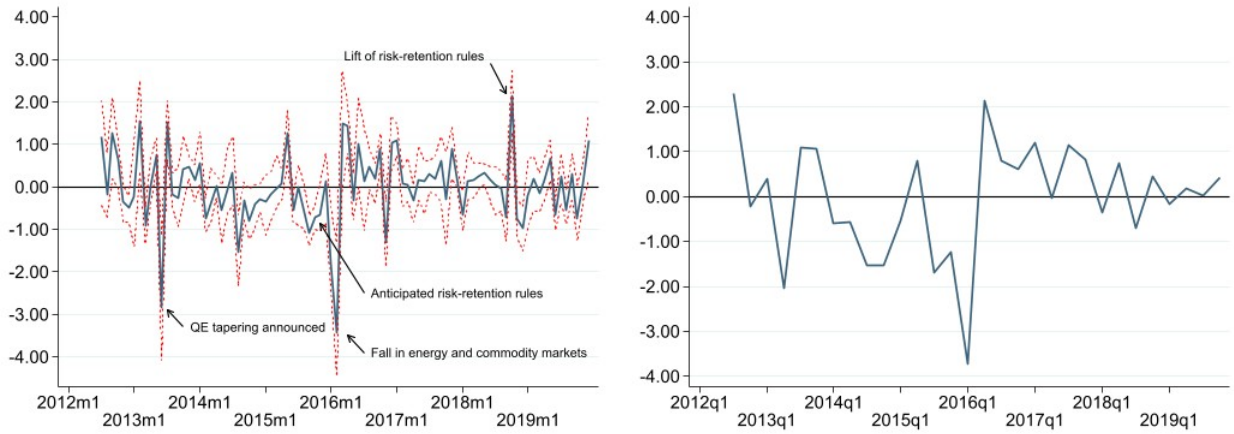
CLO Market Data. To gauge the conditions in the CLO market we use $CLODI$, the Palmer Square CLO Debt Index maintained by Bloomberg. This is a total return index of original rated A, BBB, and BB CLO debt issued after January 1, 2009, in the U.S. The index includes only cash and arbitrage CLOs backed by broadly syndicated leveraged loans.[19] As of October 31, 2021, A, BBB, and BB CLO tranches accounted for 37.5, 36.3, and 26.3% of this index, respectively.[20]

[17] Appendix B details the aggregation procedure.

[18] This step is meant to reduce the noise that banks only seldom issuing loans that could be bought by CLOs would introduce in the panel estimation. For instance, the group of 28 top banks includes a holding company that only received one institutional loan lead arranger credit during the 2012-2019 period, which makes evident that bank's business is not reliant on CLO funding.

[19] This excludes Balance Sheet CLOs and other types like Middle-Market CLOs, ABS CDOs, and Emerging Market CLOs.

[20] For further details on the index construction, see Palmer-Square-Capital-Management (2021b) and Palmer-Square-Capital-Management (2021a).



(a) Monthly Shocks

(b) Quarterly Shocks

Figure 3: Structural Institutional Investor Demand Shock in the CLO Market. Panel (a) presents the monthly structural shock identified in the VAR model. The solid blue line represents the median of the posterior distribution of the shock. The dashed red lines represent the $14th/86th$ percentile of the posterior distribution. The observations corresponding to four significant market events are indicated by the arrows. Panel (b) displays the quarterly version of the shock, which results from summing the monthly median posterior by quarter.

4 Main Results

4.1 Evidence from the VAR Structural Analysis

Before delving into the main results from the local projections, we introduce a set of outcomes that help visualize the results from the VAR model – namely, the identified structural institutional investor demand shock at monthly and quarterly frequency.

We start with the structural institutional investor demand shock at monthly frequency identified with the sign restrictions presented in Table 1. This is introduced in Panel (a) of Figure 3. The series is distributed around zero, with a standard deviation of one, and it captures the main events in the CLO market arguably well.

For instance, the large negative shock observed in June 2013 matches the announcement of the Quantitative Easing tapering by the Fed, which increased uncertainty in financial markets and severely disrupted the high-yield investment segment by causing outflows of available funds into other asset classes. The negative shocks throughout the second half of 2015 that culminated in the large negative shock in February 2016 reflect consolidations of CLO managers in anticipation of changes in risk-retention rules that took place in 2016 and concerns over loans in the energy, metals and mining sectors being downgraded.[21] In contrast, the large positive shock in October 2018 corresponds to the effects of the large wave of reset and refinance transactions caused by the repeal of the risk-retention rules in early 2018.[22]

The monthly frequency of the VAR model is very convenient for at least two reasons. First, it provides us with a suitable sample to reliably estimate a VAR model within a relatively short time span of eight years. Second, it also gives us the necessary flexibility to model the dynamics of the institutional loan and CLO markets, particularly regarding the lag structure of the model and the structural identification restrictions.

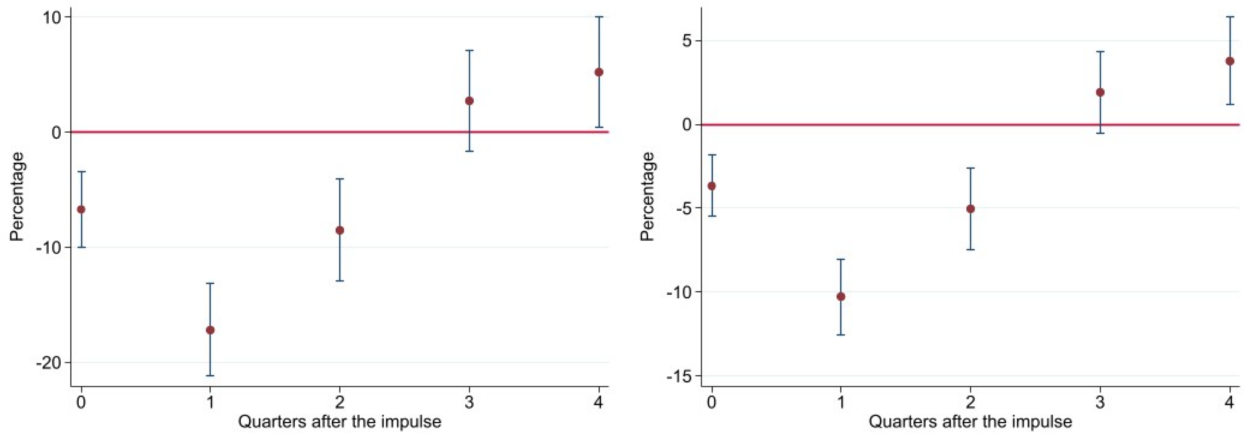
Yet, the bank-level data used in the panel analysis for the vector of control variables is only available at a quarterly frequency, provided this is the highest available frequency for accounting data from which the controls are obtained. To harmonize the frequency of both data sets, we aggregate the monthly institutional investors demand shock at quarterly frequency by summing the shocks over each quarter (as done by Holm, Paul, and Tischbirek, 2021, for instance). The result is still a zero-mean series with a slightly higher standard deviation of about 1.2, as illustrated in Panel (b) of Figure 3. A visual inspection makes it apparent that the quarterly series preserves the key events observable at monthly frequency.[23,24]

[21] As part of the Dodd-Frank Act, new risk-retention rules were imposed to the CLO market, which required managers to hold 5% of their CLOs starting from 2016. Loans in the energy, metals and mining sectors usually constitute around 5-7% of CLOs pools. The weak energy and commodity market of 2015, which reached its bottom in February 2016 with a large fall of global energy prices, triggered multiple downgrades of companies in these industries.

[22] The 2016 deals were done under the risk-retention rules at significantly higher spreads than 2018 and were subject to a 2-year non-call period. The majority of these deals reached their refinancing and reset eligibility during 2018, providing CLO managers and equity holders with the right incentives to lower the deal's liability costs. October 15th was the last date for renegotiation before year-end, since transactions can only occur on deal payment dates.

[23] An alternative approach would be to form a monthly panel and estimate local projections with versions of model (7) without bank-level controls, but enriching the lag structure of the remaining terms in the model. This alternative specification would resemble those employed, for instance, in Romer and Romer (2017). Using a monthly panel, our main results on bank riskiness remain consistent with those we obtain using the quarterly panel (see Figure A2). The monthly panel, however, does not allow us to examine other outcomes of interest and, for this reason, the quarterly panel is preferred.

[24] For completeness, we report the full set of impulse response functions for the benchmark VAR model in Figure A4. The figure clearly illustrates the identification assumptions outlined in Section 2.2. We also note that the response function of the KC Financial Stress Index to the institutional investors demand shock (bottom left panel) is negative, but small and not significant at the conventional confidence levels used in Bayesian estimation. Nevertheless, the response hints at a fall in the aggregate riskiness of the financial



(a) Benchmark: Including Time F.E.

(b) Alternative: Including S&P 500 Index

Figure 4: CLO Funding and Expected Default Frequency. Local projection of bank EDF to a one unit increase in CLO funding reliance, $\overline{E}_i \times S_t$, from the estimation of model (7). Panel (a): Benchmark EDF result, which includes time fixed effects. Panel (b): Alternative model, which includes the S&P 500 in lieu of time fixed effects. Red dots are point estimates. Blue vertical lines correspond to 90% confidence intervals.

4.2 Bank Riskiness: Evidence from the Panel Analysis

We report now the results for the impulse response functions based on the local projections from model (7). Figure 4 Panel (a) documents the average response function of EDF for the banks in our sample to a one unit increase in our measure of CLO funding, gauged by the interaction term $\overline{E}_i \times S_t$. The red dots are point estimates of the response β^j at different horizons, while the vertical blue lines represent 90% confidence intervals. The model includes bank fixed effects, time fixed effects, lagged values of the dependent variable and interaction term (with $K = 1$), and the set of lagged bank-level controls described in Section 2.3. The estimation is carried out by OLS and the standard errors are clustered at the bank level.

The results show that EDF decreases by almost 6.7% immediately upon the shock to reach a maximum fall of 17.2% one quarter from the change. After two quarters the decrease in EDF is about 8.5% and still significant, after which the effect vanishes. A simple economic interpretation of these effects can be obtained by considering the impact of a one-standard deviation shock to the institutional investor demand for CLOs, S_t, which is standardized by

sector in the wake of an increase in the institutional investor demand for institutional loans.

design. The expected default frequency of a bank would fall by about 17 basis points after a quarter for each additional percentage point in the average measure of bank exposure to CLO funding, $\overline{E}_i$.

4.3 Robustness of the Analysis

A natural concern that arises in interpreting the previous result is that lower bank EDF could mechanically be the result of a general improvement in market conditions that increases both banks' market value of equity and institutional investors funding at the same time. In other words, there might be a concern that the institutional demand shock identified in the previous stage still embeds broader liquidity effects not specifically confined to the CLO secondary market, and that these components are not fully controlled for in the baseline specification of the panel model with time fixed effects. We address this concern by directly controlling for the stock market conditions in the LP model, substituting the log of average monthly S&P 500 index for the time fixed effects in the benchmark model. Panel (b) of Figure 4 shows that implementing this alternative specification returns fairly similar results. The estimated effects are roughly a quarter smaller, but the shape and significance of the response function are not affected.

We run several additional robustness checks and obtain similar results, as reported in Appendix D. Another possible concern comes from the demand shock S_t used to form the interaction term being a synthetic variable estimated in the VAR. We check how the uncertainty around this estimate affects the local projection of EDF in Figure A1 of Appendix D. We take $1,000$ draws from the posterior distribution of S_t and recalculate $\overline{E}_i \times S_t$ for each draw. We then re-estimate the coefficients of panel model (7) and collect them in a vector for each horizon j. The figure illustrates the median of these coefficient vectors, along with confidence bands given by their $14th/86th$ percentiles. Incorporating this step also preserves the thrust of our benchmark result.

Although, as we have discussed, S_t exogeneity should suffice to identify β^j in equation (7), using a predetermined $\overline{E}_i$ could add confidence to our results. To this end we run a robustness test starting in 2013 where $\overline{E}_i$ has been estimated based on loan underwriting for 2012. That is, our proxy for reliance on the CLO market is predetermined with respect to the outcomes under analysis. Panel (a) of Figure A3 in Appendix D shows that our main findings hold for this alternative specification.

In the last robustness check we discuss here, we estimate a VAR model where an aggregate financial risk shock replaces the more generic residual shock used in the benchmark model and the average EDF of the banks in our sample replaces the Kansas City Financial Stress Index. Table A1 in Appendix D formalizes the identification restrictions of this case.[25] Panel (b) from Figure A3 in the Appendix reports the response of EDF under this alternative model. As before, EDF also falls in this case, with a response at the trough of 13% one quarter after the change in CLO funding.

Finally, we run a falsification test for the key assumption of quasi-randomly assigned shocks S_t by regressing $EDF_{i,t-1}$, the lagged outcome, on the current value of the CLO funding measure, $\overline{E}_i \times S_t$, and the controls in equation (7). Not rejecting the hull hypothesis that the $\overline{E}_i \times S_t$ coefficient in this regression is zero provides evidence in support of the orthogonality of the shock. The estimated coefficient is $-.013$ (s.e. .025), largely statistically not significant.

5 Mechanism Analysis

We now examine plausible mechanisms by which CLO funding can affect bank risk. Our analysis points to a main channel of transmission working through a change in the structure of bank balance sheets upon a shock, reducing the amount of resources banks pledge to finance loans. This adjustment results in a shift from interest-based to fee-based income origination and a temporary improvement of loan performance. Overall, banks take higher CLO funding as an opportunity to strengthen their ODT business practices, use their resources more efficiently, and lower their riskiness.

5.1 Balance Sheet Changes

The main part of the hypothesized transmission mechanism is that increasing CLO funding provides banks with incentives to originate loans meant to be funded by investors.

[25] A more detailed justification of this model is provided in Appendixes C.2 and D.4.

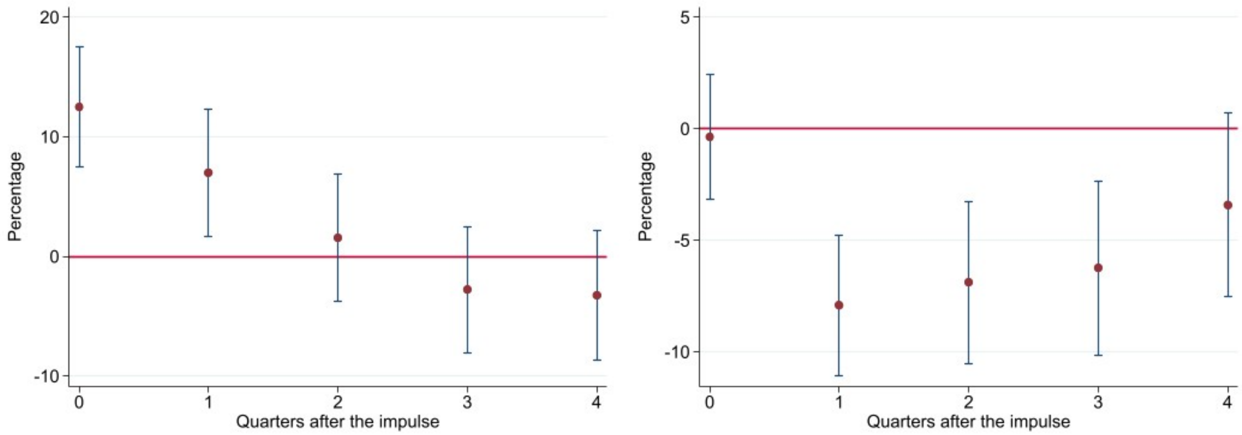
Moreover, banks could also off-load outstanding business loans from their balance sheets and replace them with new institutional loans, reducing exposure to credit risk and seeking a more efficient use of their capital. In principle, this substitution between loan types would also generate higher non-interest income from growing origination fees, helping banks improve income from lending activities relative to the size of their balance sheets. This gain in efficiency in the use of bank resources distinguishes CLO funding shocks from other forms of liquidity increases, such as a higher provision of reserves for instance, which may lead to more general expansions of bank assets across the board.

Within our panel setting, we are able to directly test the significance of this shift in the types of loans banks originate. We would expect larger effects on the institutional loan origination among banks that rely more heavily on CLO funding. Panel (a) of Figure 5 provides support to this conjecture as it shows that an increase in CLO funding causes a raise in the relative share of institutional loans origination with respect to all loans arranged by a bank for two quarters, with a peak response on impact. Previous literature also suggests that increasing CLO funding could increase the origination of institutional loans (e.g. Ivashina and Sun, 2011). Our empirical evidence is consistent with this mechanism.

We also find that the expansion in institutional lending is accompanied by a persistent fall in C&I loans held to maturity on the bank balance sheet starting from the first quarter after the shock, as Panel (b) of Figure 5 illustrates. This is consistent with banks not only marketing a larger share of the new loans they originate, but also likely selling a portion of their existing loans. The possibility of generating higher income from origination fees while employing fewer assets suggests an improvement of banks' efficiency that would lower bank risk.

5.2 Income Generation

We explore then the second part of this transmission mechanism that should take place through an adjustment of the income generation process which accompanies the change in loan structure of the bank balance sheets. A distinguished feature of the OTD model of banking is the shift from interest-based to fee-based income generation. We document in Figure 6 that a positive shock to the institutional demand for institutional loans allows banks



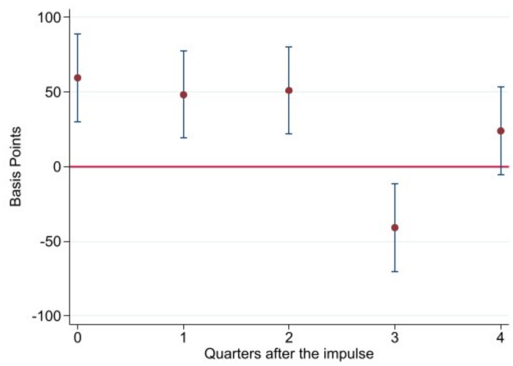
(a) Institutional Loans (b) C&I Loans

Figure 5: CLO Funding, Institutional Loan Origination and On- and Off-Balance Sheet Changes. Local projections of different outcomes of interest in response to a one unit increase in the CLO funding reliance, $\overline{E}_i \times S_t$, from the estimation of panel models specified as in (7). Panel (a): Ratio of institutional loans arranged to all loans arranged. Panel (b): Log of C&I loans held on bank balance sheet. Red dots represent point estimates. Blue vertical lines represent 90% confidence intervals.

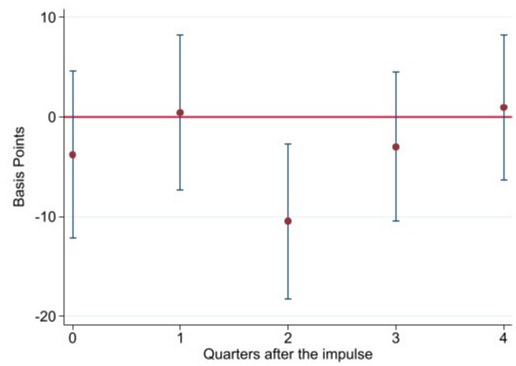
reliant on CLO funding to boost the income generated from lending-based activities relative to the total amount of resources pledged to loans in their balance sheets. This effect is driven by an intensification of the portion of income generated according to the fee-based model, despite a decrease in the portion of interest-generated income.

Panels (a) and (b) of Figure 6 respectively illustrate the responses of the ratio of non-interest and interest income to total loans. We can interpret these ratios similarly to the returns from different types of lending-related activities, in which the normalization is in terms of total loans held by a bank. Their sum, whose response is reported in Panel (c) of the figure, represents the total returns of those activities relative to the resources invested in loan assets and can be deemed as a measure of efficiency in the use if those resources.

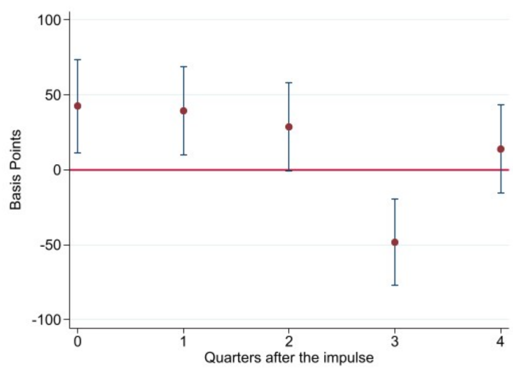
The response of the non-interest income to loans ratio to CLO funding shocks in Panel (a) is overall positive over the one-year horizon, somewhat tracing the dynamics of institutional loans in Panel (a) of Figure 5. The response initially hovers around 50 basis points and is significant for the first two quarters after a shock, but it also turns significantly negative for a period in the third quarter as the response of institutional loans to the shocks drops too.



(a) Net Non-interest Income



(b) Net Interest Income



(c) Total Income

Figure 6: CLO Funding and Income Generation. Local projections of income outcomes in response to a one unit increase in CLO funding reliance, $\overline{E}_i \times S_t$, from the estimation of panel models specified as in (7). Panel (a): Ratio of net non-interest income to lagged total loans. Panel (b): Ratio of net interest income to lagged total loans. Panel (c): Ratio of total income to lagged total loans. Red dots represent point estimates. Blue vertical lines represent 90% confidence intervals.

On the contrary, the response of the interest income to loans ratio in Panel (b) is generally negative, although milder and significant only in the second quarter after the shock. This is broadly consistent with the response of C&I loans in Panel (b) of Figure 5, and with previous evidence that shows that banks re-balance their activities in order to optimize their performance in response to changes in external factors (Goel, Lewrick, and Tarashev, 2020) and that points to a negative relationship between the evolution of interest and non-interest income (Brunnermeier, Dong, and Palia, 2020).

Finally, the drop of the net interest income is smaller in absolute value than the increase in the net non-interest income which leads to a total effect of the shock that closely follows the response of non-interest income, as reported in Panel (c). The total effect corresponds to a net improvement in the income generation process, especially in the first part of the response after the shock, which helps explain the behavior of bank riskiness outlined in our benchmark results in Figure 4.

5.3 Loan Performance

As a last piece of the mechanism analysis, and motivated by previous literature studying the performance of loans sold or otherwise securitized, we explore the role of loan performance in the transmission mechanism.

On the one hand, excess institutional investor demand could cause banks to relax their loan screening and monitoring practices. This effect would lead to poorer loan performance and could increase bank riskiness if banks fail to manage loan credit risks effectively. On the other hand, increasing CLO demand for institutional loans could give banks an opportunity to restructure their nonperforming loan portfolios, reducing bank riskiness.

We empirically address this point by studying the response of C&I loan delinquency to the CLO funding shock. Figure 7, which centers on nonaccrual delinquent C&I loans, suggests that the CLO funding shock temporarily reduces the weight of delinquent loans on the bank balance sheets for up to two quarters upon the shock, although the effect is only statistically marginally significant. We can suggest two alternative, not mutually exclusive, mechanisms to explain this result.

The first is that increasing availability of CLO funding gives banks the opportunity to originate new loans used to refinance nonperforming credits, along the lines of the zombie lending or ever-greening effects documented in the literature (see, for instance, Hu and Varas, 2021; Bonfim, Cerqueiro, Degryse, and Ongena, 2020). The second explanation is that increasing availability of CLO funding simply gives banks the opportunity to offload nonperforming loans to the market.

This opportunistic bank behavior would share some insights with the literature showing that banks sell different types of loans depending on specific circumstances. For instance, Irani, Iyer, Meisenzahl, and Peydró (2021) document that undercapitalized banks are more likely to sell nonperforming loans, provided their higher risk weights for capital requirements.

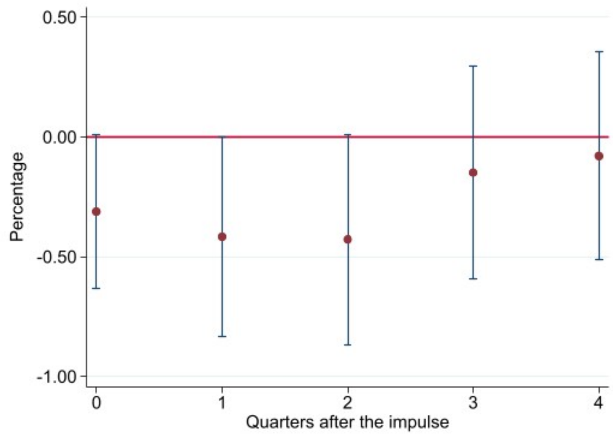


Figure 7: CLO Funding and Loan Performance. Local projections of Delinquent nonaccrual C&I loans, scaled by C&I loans, in response to a one unit increase in CLO funding reliance, $\overline{E}_i \times S_t$, from the estimation of a panel model specified as in (7). Red dots represent point estimates. Blue vertical lines represent 90% confidence intervals.

Still, while both of the preceding arguments seem ex-ante plausible, further investigation is required to more clearly depict this mechanism.

6 Conclusion

We study the causal effect of CLO funding on bank riskiness. Our main contribution is to show that positive CLO funding shocks can reduce bank probability of default for half a year.

We also explore plausible mechanisms that can help explain the main result. We conclude that heightened CLO funding allows banks to restructure their balance sheets by increasing the origination of institutional loans, while retaining lower amounts of loans on their balance sheets despite the increase in origination. This provides banks with a way to strengthen net non-interest income and more efficiently use resources. The performance of the loans that banks choose to retain also temporarily improves, which can further strengthen their financial positions.

Our results contribute to the literature on bank risk management, primarily providing the identification of a causal link between CLO funding and bank riskiness. They also contribute to the literature studying the shadow banking system and how it affects the performance of banks. Ultimately, our paper informs the policy-making process, providing relevant insights about the effects of loan securitization to bank regulators and supervisors.

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Appendix

A Variable Definitions and Sources

Dependent Variables for Local Projections Analysis

The following dependent variables come from own elaboration using the data sources cited below.

- *EDF*. Own elaboration, following the procedure described in Bharath and Shumway (2008), using data from CPST, CRSP, FRED.

- Institutional loan origination, used in Panel 5a. The quarterly ratio of institutional loans led to all loans led by a bank, on a proportional basis. For each loan arranged, a portion is asigned to a bank, which is the inverse of the number of banks arranging the loan. Suppose, for instance, that bank A arranges two loans during quarter t: institutional loan I and non-institutional loan N. Loan I is co-arranged with another bank B, so A is asigned 1/2 institutional loan. Loan N is arranged solely by A instead, so A is asigned 1/1 non-institutional loan. Then, this institutional loan origination measure for bank A in quarter t is $0.5/(0.5 + 1) = 1/3$. Elaborated with data from DealScan.

The following dependant variables come from the FR Y-9C Report.

- Log of C&I loans: LN(BHDM1766).

- Net noninterest income to lagged equity: (quarterly change of BHCK4079 - quarterly change of BHCK4093) / LAG1.BHCK3210.

- Investment banking, advisory, and underwriting fees and commissions to lagged equity: quarterly change of BHCKC888 / LAG1.BHCK3210.

- Net interest income to lagged equity: quarterly change of BHCK4074 / LAG1.BHCK3210.

- Delinquent nonaccrual C&I loans to C&I loans: BHCK1608 / BHDM1766.

- Trading C&I loans to C&I loans: BHCKF614 / BHDM1766.
- All C&I past due to C&I loans: (BHCK1606 + BHCK1607 + BHCK1608) / BHDM1766.
- Past due C&I loans still accruing to C&I loans: (BHCK1606 + BHCK1607) / BHDM1766.

Control Variables for Local Projections Analysis

The following control variables come from the FR Y-9C Report.

- Real estate loans to total loans: BHCK1410 / BHCK2122.
- Commercial & industrial loans to total loans: BHDM1766 / BHCK2122.
- Deposits to total assets: (BHDM6631+BHDM6636+BHFN6631+BHFN6636) / BHCK2170.
- Noninterest income to net operating revenue: quarterly change of BHCK4079 / (quarterly change of BHCK4079 + quarterly change of BHCK4074).
- Log of total assets: LN(BHCK2170).
- Growth rate of total loans: LN(BHCK2122) - LN(LAG1.BHCK2122).
- Balance sheet liquidity: securities available for sale plus federal funds sold in domestic offices and securities purchased under agreements to resell, all scaled by total assets. (BHCK1773+ BHDMB987+BHCKB989) / BHCK2170.
- Equity to total assets: BHCK3210 / BHCK2170.

The following is market data used in a robustness check.

- S&P 500 index. Log of quarterly average of S&P 500.

Time Series Variables for VAR Analysis

- CLODI, Palmer Square CLO Debt Index. Palmer Square produces two related indices: the Palmer Square CLO Senior Debt Index (CLOSE) and Palmer Square CLO Debt Index (CLODI). According to the firm, these indices *"seek to reflect the investable universe for U.S. dollar denominated collateralized loan obligations... CLODI is comprised of original rated A, BBB, and BB debt issued after January 1, 2009 subject to certain inclusion criteria... Both indices are comprised solely of cash and arbitrage CLOs backed by broadly syndicated leveraged loans."* (Palmer-Square-Capital-Management, 2018) Used in logs. Source: Bloomberg.

- Financial system EDF. Own elaboration, as described in the text, using data from CPST, CRSP, FRED. This time series is the monthly average of the EDF for all U.S.-based financial companies – Standard Industrial Classification (SIC) codes between 6000 and 6999.

- Kansas City Financial Stress Index. Source: FRED.

- Institutional loans volume. The monthly sum of the amount of all institutional loans (term loan B through term loan K) originated to U.S. firms, in U.S. dollars, syndicated in the U.S. Seasonally adjusted and used in logs. Source: DealScan.

- Institutional loans all-in-spread drawn. The monthly average of All-In Drawn spread on all institutional loans (term loan B through term loan K) originated to U.S. firms, in U.S. dollars, syndicated in the U.S. Source: DealScan.

B Identifying Lead Arrangers and Aggregating them at the Top Bank Holding Company (BHC) or Financial Holding Company (FHC)

Estimating bank reliance on CLO funding starts with defining those banks that lead institutional loans, defined as facilities named Term Loan B through Term Loan K, and likely to be part of the group of loans referred to as Broadly Syndicated Loans (BLS). A bank is defined as a transaction lead lender if it receives Lead Arranger Credit in DealScan.

A financial institution can act as lead arrenger through different subsidiaries. For instance, DealScan records loans led by several arms belonging to the Domestic Financial Holding Company *"Goldman Sachs Group, Inc., The,"* including *"Goldman Sachs & Co."* (since Apr/2017 legally called *"Goldman Sachs & Co. LLC."*) and *"Goldman Sachs Bank USA."*

The process of estimating bank reliance on CLO funding requires that we aggregate all loan originations from a same top domestic financial institution. We start by identifying all lead arrangers leading at least 50 transactions during the 2012-2019 sample period and then consolidate all the related lead arrangers partaining to the same top institution. Our focus is on those cases where the top financial institution is either a Domestic Bank Holding Company (BHC) or a Domestic Financial Holding Company (FHC).

In order to consolidate transactions at the BHC/FHC level, we rely on a number of sources of information. The first source is DealScan itself, which records parent and ultimate parent company information for a given bank. While this is often a good starting point in the aggregation process, it is not necessarily entirely accurate in all cases. A key reason being that this mapping only reflects the latest bank-parent-ultimate parent relationship recorded by DealScan – i.e. it does not keep track of historical relationships. For instance, a given bank could be sold from one BHC/FHC to another one at some point in time, and the record in DealScan would only reflect the latest relationship established. To address this and other possible information gaps, we resort to the National Information Center to identify the lead arranger and link it to the relevant top BHC/FHC over time, which requires studying the financial institution history and the hierarchical organization. Often, this process also requires searching for information that helps us depict the evolution of the different bank relationships, particularly in what regards consolidations. Thus, we complement the previous sources with news, SEC filings available from EDGAR, corporate announcements, general information available on the *Investor Relations* sections of the banks' websites, and other sources of information that can help us obtain a clear picture of the BHC/FHC structure over time. It is also during this step that we consolidate at the BHC/FHC also smaller subsidiaries which might have led fewer than 50 transactions. Lastly, when possible, we cross-validate our matchings with other matchings previously established in the literature (specifically, those made by Barraza, Lee, and Yeager, 2015; Schwert, 2018).

We emphasize lastly that our choice to work with *Domestic* BHC and FCH stems from the need to work with comparable banking organizations, particularly in what regards financial regulation. Riskiness and the different measures of it we can think of are intrinsically related to the regulatory requirements banks are subject to, and Domestic and Foreign institutions operating in the United States have been subject to (sometimes significantly) different requirements over time, which renders infeasible a meaningful comparison between these two types of institutions.

C Considerations on the Shift-Share Approach

C.1 Borusyak, Hull, and Jaravel (2022)'s Shock Orthogonality Condition for Panel Models

The benchmark case. We begin this section by reporting the baseline Borusyak, Hull, and Jaravel (2022)'s orthogonality condition at shock-level for an IV cross-section regression. For sake of convenience, we adopt the same notation as theirs. The IV moment condition reads:

$$\mathbb{E}\left[\sum_l e_l z_l \varepsilon_l\right] = 0, \tag{A1}$$

where ε_l are the residuals of the regression, e_l represents the overall economic weight of unit l, and z_l is the instrumental variable defined by the mix of shocks g_n, using as weights the exposure share of unit l to shock n, $s_{l,n}$:

$$z_l = \sum_n s_{l,n} g_n. \tag{A2}$$

Note that the overall weight of shock n across all units is defined as s_n:

$$s_n = \sum_l e_l s_{l,n}. \tag{A3}$$

We can rewrite (A1) by using (A2) and (A3) and rearranging the summation indexes as an orthogonality condition at shock-level:

$$\mathbb{E}\left[\sum_l e_l z_l \varepsilon_l\right] = \mathbb{E}\left[\sum_l e_l \left(\sum_n s_{l,n} g_n\right) \varepsilon_l\right] = \mathbb{E}\left[\sum_n g_n \sum_l e_l s_{l,n} \varepsilon_l\right] =$$
$$\mathbb{E}\left[\sum_n g_n \left(\sum_l e_l s_{l,n}\right) \frac{\sum_l e_l s_{l,n} \varepsilon_l}{\sum_l e_l s_{l,n}}\right] = \mathbb{E}\left[\sum_n g_n s_n \bar{\varepsilon}_n\right] = 0, \tag{A4}$$

where the aggregate shock-level residual of the cross-section model, $\bar{\varepsilon}_n$, is defined as the weighted average of the unit-level residuals, ε_l, using weights given by the unit shares adjusted by $e_l s_{l,n}$:

$$\bar{\varepsilon}_n = \frac{\sum_l e_l s_{l,n} \varepsilon_l}{s_n}, \tag{A5}$$

and $s_n = \sum_l e_l s_{l,n}$.

The panel case. We now express the orthogonality condition for the panel regression and with only one shock. Following Section 4.3 of Borusyak, Hull, and Jaravel (2022), let us first define the following terms:

- Composite indexes for unit and shocks that include periods: $\tilde{l} = (l, t)$ and $\tilde{n} = (n, \tau)$.
- Time-varying unit exposure shares: $\tilde{s}_{\tilde{l},\tilde{n}} = s_{l,n,t} \mathbb{1}_{t=\tau}$, where $\mathbb{1}_{t=\tau}$ is an indicator function that select the share when $t = \tau$.
- A time-varying instrument: $z_{\tilde{l}} = \sum_{\tilde{n}} \tilde{s}_{\tilde{l},\tilde{n}} g_{\tilde{n}}$, where we have an instrument for each period and unit (l, t).

We can write condition (A4) for this case as:

$$\mathbb{E}\left[\sum_{\tilde{l}} e_{\tilde{l}} z_{\tilde{l}} \varepsilon_{\tilde{l}}\right] = \mathbb{E}\left[\sum_{\tilde{l}} e_{\tilde{l}} \left(\sum_{\tilde{n}} \tilde{s}_{\tilde{l},\tilde{n}} g_{\tilde{n}}\right) \varepsilon_{\tilde{l}}\right] = \mathbb{E}\left[\sum_{\tilde{n}} g_{\tilde{n}} \sum_{\tilde{l}} e_{\tilde{l}} \tilde{s}_{\tilde{l},\tilde{n}} \varepsilon_{\tilde{l}}\right] =$$
$$= \mathbb{E}\left[\sum_{\tilde{n}} g_{\tilde{n}} \left(\sum_{\tilde{l}} e_{\tilde{l}} \tilde{s}_{\tilde{l},\tilde{n}}\right) \frac{\sum_{\tilde{l}} e_{\tilde{l}} \tilde{s}_{\tilde{l},\tilde{n}} \varepsilon_{\tilde{l}}}{\sum_{\tilde{l}} e_{\tilde{l}} \tilde{s}_{\tilde{l},\tilde{n}}}\right] = \mathbb{E}\left[\sum_{\tilde{n}} g_{\tilde{n}} \tilde{s}_{\tilde{n}} \bar{\varepsilon}_{\tilde{n}}\right] = 0, \tag{A6}$$

which after expanding the summations over the composite indexes also reads:

$$\mathbb{E}\left[\sum_n \sum_\tau g_{n,\tau} \tilde{s}_{n,\tau} \bar{\varepsilon}_{n,\tau}\right] =$$
$$= \mathbb{E}\left[\sum_n \sum_\tau g_{n,\tau} \left(\sum_l \sum_t e_{l,t} s_{n,l,t} \mathbb{1}_{t=\tau}\right) \frac{\sum_l \sum_t e_{l,t} s_{n,l,t} \mathbb{1}_{t=\tau} \varepsilon_{l,t}}{\sum_l \sum_t e_{l,t} s_{n,l,t} \mathbb{1}_{t=\tau}}\right] = 0. \tag{A7}$$

Condition (A7) illustrates the shock-level orthogonality condition when multiple cross-sections are considered – the shocks must be orthogonal to share-weighted, shock-level average residuals of the panel over time.

In our empirical application, some assumptions further simplify the expression of condition (A7). Specifically, all exposure shares $s_{n,l,t}$ and regression weights $e_{l,t}$ are made time invariant and only one shock is considered ($n = 1$). Under these assumptions, (A7) becomes:

$$\mathbb{E}\left[\sum_{\tau} g_{\tau}\left(\sum_{t} \mathbb{1}_{t=\tau}\sum_{l} e_l s_l\right)\frac{\sum_t \mathbb{1}_{t=\tau}\sum_l e_l s_l \varepsilon_{l,t}}{\sum_t \mathbb{1}_{t=\tau}\sum_l e_l s_l}\right] = \mathbb{E}\left[\sum_{\tau} s g_{\tau}\overline{\varepsilon}_{\tau}\right] = 0, \tag{A8}$$

where $s = \sum_t \mathbb{1}_{t=\tau}\sum_l e_l s_l = \sum_l e_l s_l$ and, with a small abuse of notation, $\overline{\varepsilon}_{\tau} = \frac{\sum_t \mathbb{1}_{t=\tau}\sum_l e_l s_l \varepsilon_{l,t}}{s}$ corresponds to the exposure share-weighted, shock-level average residual extracted for period τ by the index function $\mathbb{1}_{t=\tau}$.

The requirements for estimation consistency. Condition (A8) is the orthogonality condition of the shocks and shock-level aggregate panel residuals expressed over the periods of the sample. This condition informs the assumptions required for consistency of the estimates of model (7) in the main text of the paper:

- $\mathbb{E}\left[s^2\right] \to 0$ for L (and T) $\to \infty$, and an effective large sample (T large) for the shock-level regression (A8).
- Conditional quasi-random assignment of shock g_{τ}, given the series of shock-level residuals $\overline{\varepsilon} = \{\overline{\varepsilon}_{\tau}\}_{\tau}$, s, and the series of shock-level controls $q = \{q_{\tau}\}_{\tau}$ which notably include unit and period fixed effects: $\mathbb{E}\left[g_{\tau}|\overline{\varepsilon}, s, q\right] = q'_{\tau}\mu$ for all τ.
- Uncorrelated (demeaned) shocks across any pair of periods, conditional on $\overline{\varepsilon}$, s, q

C.2 The Condition with EDF in the VAR Model

In a slightly different approach in one of our robustness checks reported in Section D.4, we modify the VAR model used to construct S_t by replacing the Kansas City Financial Stress Index with the exposure share-weighted aggregate EDF. In this way, we can construct a shock that aims to directly satisfy the moment condition (A8) in the panel regression, instead of simply relying on the Borusyak, Hull, and Jaravel (2022)'s consistency assumptions about g_t.

Let us define then $EDF_t = \sum_l s_l EDF_{l,t}$, where $EDF_{l,t}$ is the expected default risk of bank l in period t. We add EDF_t to the VAR and use the identification strategy of the structural shocks illustrated in more detail in Section D.4 and in Table A1. The EDF_t is then modeled as a function of the lags of the endogenous variables of the VAR, which include the autoregressive terms of EDF_t itself, and the reduced-form residual u_t^{edf}, which embeds the structural shocks explicitly modeled for the institutional loan market dynamics $\left[w_t^{InstD}, w_t^{BankS}, w_t^{CorpD}\right]$ and a fourth shock $w_t^{FinRisk}$ capturing overall financial riskiness, which can influence loan decisions and bank riskiness but through factors distinguished from the institutional investor demand shocks for CLOs.

In particular, we can decompose u_t^{edf} into

$$u_t^{edf} = A_0(4,:) \left[w_t^{InstD}, w_t^{BankS}, w_t^{CorpD}, w_t^{Resid}\right]', \tag{A9}$$

where $A_0(4,:)$ is the last row of A_0, the impact matrix identifying the VAR structural shocks defined in equation (6) of the paper.

After controlling for $\overline{E}_i \times S_t$, all the bank-level control variables, unit and period fixed-effects, the panel model (7) likely captures the effects of w_t^{InstD}, w_t^{BankS}, w_t^{CorpD}, and most of the other structural components contained in $w_t^{FinRisk}$ and not explicitly modeled in the VAR, leaving a shock-level aggregate panel residual $\overline{\varepsilon}_t$ which can be now interpreted mostly as a sub-component of $w_t^{FinRisk}$. Under the identifying assumption of the structural VAR, w_t^{InstD} is orthogonal to $w_t^{FinRisk}$, and its components, and it would also be orthogonal to $\overline{\varepsilon}_t$, therefore satisfying condition (A8) as well.

D Robustness Checks for the Benchmark Result

D.1 Accounting for Uncertainty in the Estimation of Shock S_t

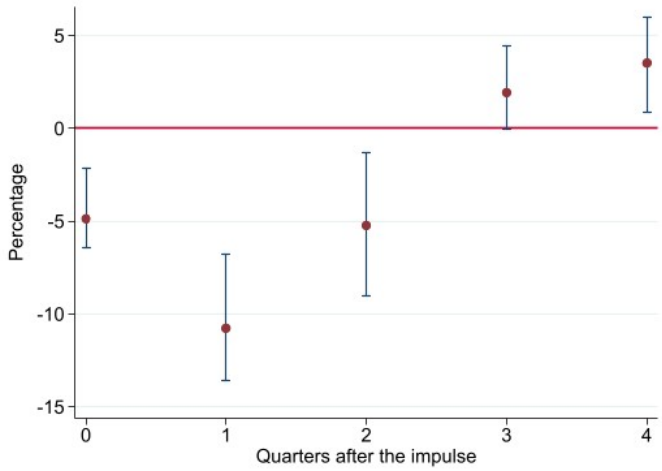


Figure A1: Response of EDF – benchmark model. The confidence bands are constructed by Monte Carlo simulation taking $1,000$ draws from the posterior distribution of S_t, recalculating $\overline{E}_i \times S_t$, and re-estimating the coefficients β^j in panel model (7). For each horizon j, the red dots represent the median of the vector of the $1,000$ estimated coefficients, while the blue vertical lines correspond to the $14/86th$ percentiles of the vectors.

D.2 EDF Response using Monthly Data

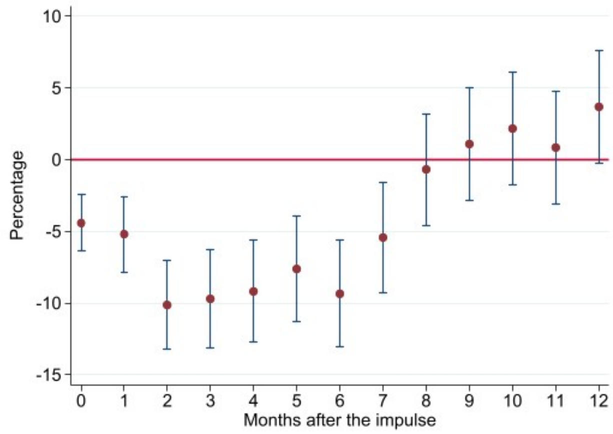


Figure A2: CLO Funding and Expected Default Frequency. Local projections of bank EDF to a one unit increase in CLO funding reliance, $\overline{E}_i \times S_t$, from the estimation of model (7). The model is estimated at monthly frequency (months on the horizontal axis). Red dots are point estimates. Blue vertical lines correspond to 90% confidence intervals.

In this section we use the local projections method to estimate the response of EDF to CLO funding shocks at monthly frequency. Given the high-frequency of the data, we cannot control for bank characteristics which we only have at quarterly frequency. Hence, the model equation (7) is simplified to exclude the vector $X_{i,t-1}$. This model follows in spirit the main specification in Romer and Romer (2017) and we estimate it using three-month lags, for a horizon of up to one year.

The response of EDF, presented in Figure A2, resembles that in the benchmark result reported in Figure 4 above. That is, the peak response takes place between the first two quarters after the shock. A similar test using the log of S&P 500 in lieu of time fixed effects yields similar results.

D.3 Predetermined Reliance on CLO Market Funding

In this robustness exercise we use a predetermined exposure to the institutional investors demand shock in the CLO market. To this end, we estimate $\overline{E}_i$ based solely on loan underwriting during 2012. We then use this exposure to estimate the local projections for outcomes of interest between 2013 and 2019. Panel (a) of Figure A3 displays the corresponding results for EDF.

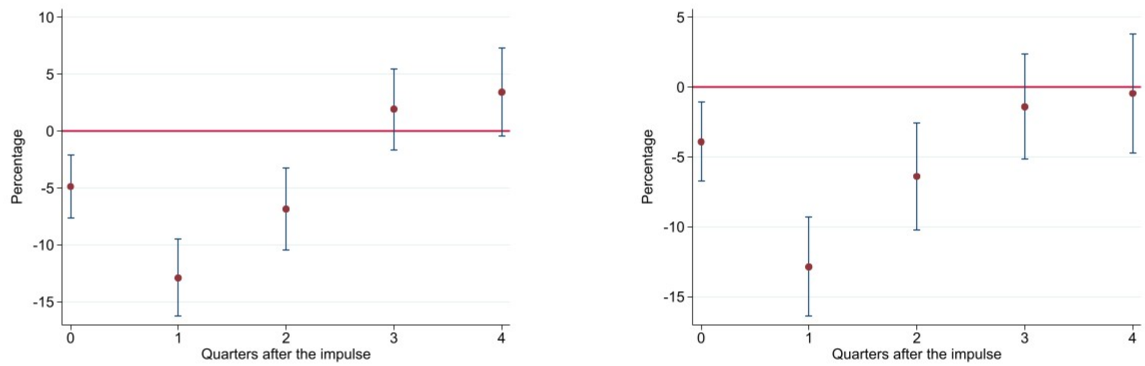
D.4 Alternative Identification of Institutional Investors Demand Shock

$$\begin{bmatrix} u_t^{clo} \\ u_t^{vol} \\ u_t^{spr} \\ u_t^{edf} \end{bmatrix} = \begin{bmatrix} + & - & - & - \\ + & + & + & - \\ - & - & + & + \\ 0 & * & * & + \end{bmatrix} \begin{bmatrix} w_t^{InstD} \\ w_t^{BankS} \\ w_t^{CorpD} \\ w_t^{FinRisk} \end{bmatrix}$$

Table A1: Identifying restrictions of the monthly structural shocks of the VAR model. The four shocks identified are an institutional investor demand shock for institutional loans w_t^{InstD}, a bank supply shock w_t^{BankS}, a corporate demand shock w_t^{CorpD}, and an aggregate financial sector risk shock $w_t^{FinRisk}$. The symbols $+/-$ indicate a positive/negative on-impact sign restriction, 0 indicates an on-impact zero restriction, and $*$ indicates unrestricted coefficients.

In an alternative strategy to identify the institutional investors demand shock, we replace the Kansas City Financial Stress Index with the the average EDF of the banks in our sample and identify an aggregate financial risk shock to substitute the residual shock employed in the benchmark strategy.

With respect to the sign restrictions used in the benchmark VAR model presented in the main text, we introduce two main variations. Firstly, we explicitly establish that the institutional demand shock for CLOs affects bank riskiness only with a lag, and we impose the restriction $A(4,1) = 0$ on matrix A_0. A way to think about this assumption is that this structural shock does not directly affect individual bank riskiness, but only through banks' reliance on CLO funding, plausibly allowing for a delayed transmission at



(a) Pre-determined $\overline{E}_i$ (b) C&I Loans

Figure A3: Local projections for Robustness Checks Models. Local projection of a bank EDF to a one unit increase in CLO funding reliance, $\overline{E}_i \times S_t$, from the estimation of model (7). Panel (a): Predetermined reliance on institutional loan origination in $\overline{E}_i \times S_t$. Panel (b): Institutional investors' demand shock recovered from the alternative VAR model summarized in Table A1. Red dots are point estimates. Blue vertical lines correspond to 90% confidence intervals.

monthly frequency and, hence, shutting down the contemporaneous effect in A_0. Secondly, the overall financial risk shock is assumed to lower the price of CLOs, lower loan issuance, increase loan spreads, and increase the aggregate riskiness of the banking sector – fourth column on matrix A_0. As illustrated by Table A1, financial risk and institutional demand shocks are assumed to have the same effects on the CLO market components of the reduced VAR model. The identification of these two structural shocks, then, crucially relies on the restriction $A(4, 1) = 0$, which is used to fully disentangle them. Table A1 summarizes the overall identification strategy, while Panel (b) Figure A3 presents the local projection results from the estimation of model (7) for this case.

E Additional Tables and Figures

Lead Arrangers and their Reliance on CLOs

Financial Institution	$\overline{E}_i$
Ally Financial Inc.	17.6
Bank Of America Corporation	13.8
Capital One Financial Corporation	7.8
CIT Group Inc.	9.4
Citigroup Inc.	19.6
Citizens Financial Group, Inc.	13.0
Fifth Third Bancorp	11.1
Goldman Sachs Group, Inc., The	40.7
JPMorgan Chase & Co.	13.6
Keycorp	9.9
M&T Bank Corporation	6.8
Morgan Stanley	41.6
Suntrust Banks, Inc.	16.3
SVB Financial Group	8.6
Webster Financial Corporation	13.6
Wells Fargo & Company	8.3
Average	15.7
S.D.	10.6

Table A2: Reliance on CLO funding $\overline{E_i}$ ($\times$100) for domestic BHC and FHC with at least fifty transactions led during the sample period 2012-2019. Reliance on CLO funding is constructed as described in the main text.

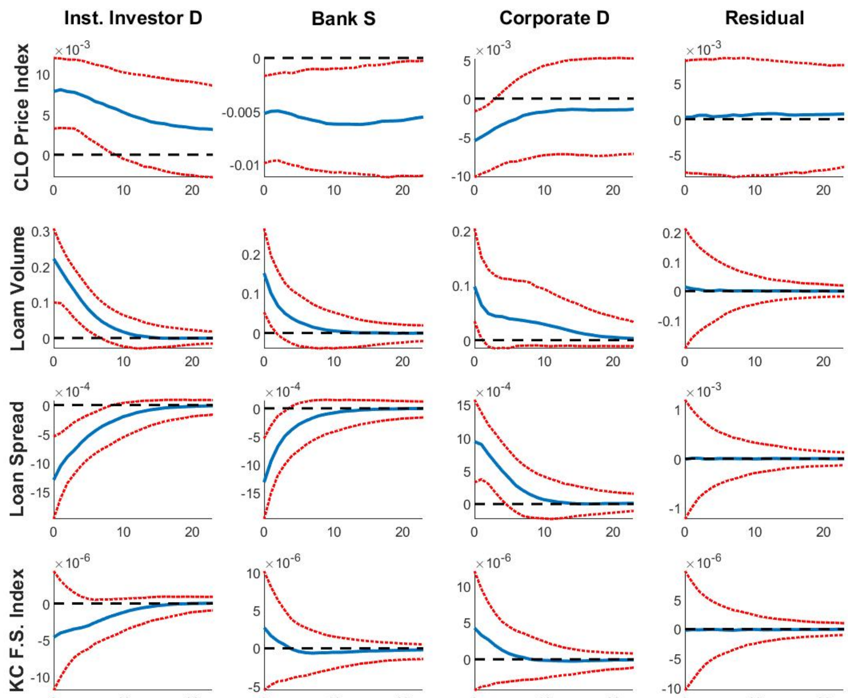


Figure A4: Response Functions of the Benchmark VAR model. Responding variables are reported by row. Shocks are reported by column. The structural shocks are identified by the assumptions in Table A1. One-standard deviation shocks are considered. The blue line is the median posterior response to the shock. The dashed-red lines are the $14th/86th$ posterior bands. The unit of time on the horizontal axis is months.